Links between Adolescents' Deep and Surface Learning Approaches, Problematic Internet Use, and Fear of Missing Out (FoMO)

Dorit Alt*, Meyran Boniel-Nissim

Kinneret College on the Sea of Galilee, Tzemach Junction, MP Jordan Valley 15132, Israel

ARTICLE INFO

ABSTRACT

This study was aimed at exploring links between adolescents' deep and surface approaches to learning, Fear of Missing Out (FoMO), and Problematic Internet Use (PIU) by using Partial Least Squares Structural Equation Modeling (PLS-SEM). The analysis corroborated the postulated positive links between surface learning, FoMO, and PIU. Moreover, the FoMO construct represented a complimentary mediation between the surface learning approach and PIU constructs. This study may lead to a plausible inference according to which both FoMO and surface learning share a common core characteristic of decreased levels of self-regulation that might lead to PIU. Having students acquire and practice skills of self-regulation might help them control their levels of FoMO, and consequently their PIU at schools or out-of-school learning environments.

1. Introduction

Adolescent students are heavy users of social media tools relative to the general population and use them extensively for leisure, communication with peers, and learning (Lenhart et al., 2015a). The characteristics attributed typically to 'net generation' students are information technology mindset and highly developed multitasking skills (Carlisle et al., 2016). Previous work showed positive links between Internet information seeking and higher academic performance among high school students (Chen et al., 2014). However, Internet use may become problematic for students who are unable to control their activities (Wąsiński and Tomczyk, 2015).

Recently, several studies have raised awareness to a new phenomenon termed Fear of Missing Out (FoMO), associated with such Problematic Internet Use, specifically related to social media excessive use (Alt, 2015, 2016, 2017a, 2017b). FoMO is characterized by the desire to stay continually connected with what others are doing (Przybylski et al., 2013). In those studies, FoMO was found related to deficit in psychological needs, a-motivation for learning, poor adjustment to college life, and was linked to excessive use of social media platforms for activities unrelated to learning during lessons. With the growing attention paid to the connection between PIU by technology-enabled tools, learning underperformances, and FoMO, and the minimal attention devoted to understanding these connections among adolescents, it seems worthwhile to test how PIU and FoMO correlate with adolescents' deep and surface approaches to learning.

This study could give new insights into possible associations between FoMO, PIU, and approaches to learning, and could raise educators' awareness toward possible similar features characterizing FoMO and surface learning, which might be useful to detect both phenomena and their contribution to PIU.

2. Literature review

2.1. Problematic use of social media tools

Due to the widespread options of connecting online (through smartphone, tablet, computer, etc.), the Internet has become central in adolescents' lives, as they use it for leisure (e.g., listening to music, watching movies, playing online games), communication (with friends and family), and learning (school tasks, general knowledge; Carlisle et al., 2016; Wu and Chen, 2015). Several studies have examined the relationships between Internet use and academic performance, indicating positive links between the latter and Internet information seeking among high school students (Chen et al., 2014; Zhu et al., 2011). The American Pew Research Center (Lenhart et al., 2015a) reported that 92% of 13–17-year-old teenagers go online daily, with 24% using the Internet "almost constantly", and 56% connecting "several times a day". In addition, 91% of the teenagers reported going online using a mobile device. In the same route, according to an Israeli study (Sasson et al., 2012), 91% of the teenagers reported using social network sites, and 71% send or receive instant messages.

The unique characteristics of the Internet, which make it attractive, are availability, accessibility, affordability, and anonymity (Greenfield,

1999). Moreover, the possibility to communicate with others results in a strong and intense commitment to stay online. A recent survey (Lenhart et al., 2015b) showed that 80% of teenagers admit they use texting as the most common way to get in touch with their friends. Feeling socially connected and accepted can be rewarding for adolescents. However, these characteristics can, in turn, promote Problematic Internet Use behaviors (van den Eijnden et al., 2010; Young, 1998). The combination of adolescence and the unique characteristics of the cyberspace put teenagers at risk for Problematic Internet Use. Developmental changes during adolescence involving pubertal maturation, continuing brain development, adolescents' sensitivity to stimulation, changing relationship with parents, and an expanding social peer environment, all contribute to a peak period of risk for the early onset of addictive behaviors (Chung, 2013).

However, Internet use is not necessarily indicative of problematic use. It may become problematic only for those who are unable to control their online activities. Addicted individuals abandon their everyday activities and devote their time to the activities that they discover on the Internet (Wąsiński and Tomczyk, 2015). Problematic Internet Use (PIU) refers to the "use of the Internet that creates psychological, social, school and/or work difficulties in a person's life" (Beard and Wolf, 2001, p. 378). Meaning that high levels of Internet use could interfere with daily life and well-being, reduce school performance, cause sleep deprivation, and result in social withdrawal and family problems (Flisher, 2010; Siciliano et al., 2015).

The literature on problematic Internet addiction shows high comorbidity of Internet addiction with psychiatric disorders, especially affective disorders (including depression), anxiety disorders (generalized anxiety disorder, social anxiety disorder), and attention deficit hyperactivity disorder (ADHD). Several factors are predictive of PIU, including personality traits, parenting and familial factors, alcohol use, and social anxiety (Chen et al., 2016; Kim and Jeong, 2015; Weinstein and Lejoyeux, 2010).

PIU has different designations within the research literature: Internet addiction, Internet overuse, compulsive Internet use, excessive Internet use, pathological Internet use, and Internet dependency. However, Internet addiction disorder still has not been entered in the Diagnostic and Statistical Manual. The American Psychiatric Association has proposed it as a possible nonsubstance addiction within the DSM-5 category Substance Use and Addictive Disorders (American Psychiatric Association [APA], 2013). Moreover, this phenomenon is still under evaluation, due to the fast progress of Internet accessibility and usability, which forces us to understand the accurate definition of Internet addiction. A systematic review of 658 articles related to the emergent area of PIU research (Moreno et al., 2011), revealed that the evaluation of this phenomenon is hampered by methodological inconsistencies. In the present study, the term that will be used is PIU as it is related to the increased risk of addiction to the digital world among adolescents (Siciliano et al., 2015).

Among other correlates such as online gaming (Qiaolei, 2014; van Rooij et al., 2014), and social networking (Ryan et al., 2014; van den Eijnden et al., 2016), previous work connected the level of internet addiction to academic performance decrement (Qiaolei, 2014). Adolescents with PIU spend excessive amounts of their time on the Internet and fail to manage their time efficiently. As expected, the consequences for the adolescents involved are poor school attendance and neglect of academic work, lower grades and academic dismissal (Chen and Tzeng, 2010; Huang and Leung, 2009). Moreover, research has also indicated that adolescents who feel connected to school are less likely to develop PIU (Li et al., 2013). These studies' findings are consistent with those of Akhter (2013) who assessed the relationship between Internet addiction and academic performance among university undergraduates. The results showed an inverse relation between Internet addiction and academic performance. Mishra et al. (2014) also aimed at capturing data from a wide variety of college students to determine the various guises of Internet addiction, and the potential consequences of unfettered

access with the Grade Point Average (GPA) as the final measure of success or failure. The results indicated that there is an inverse relationship between the degree of Internet addiction and academic success. Similarly, Türel and Toraman (2015) have assessed the relationship between the Internet addiction level of secondary school students and their academic performances. Their findings showed that Internet addiction was inversely related to academic achievements of students.

2.2. Fear of Missing Out (FoMO)

The above-mentioned literature is mainly focused on defining and measuring PIU that might *lead* to psychological, social, school and/or work difficulties (Beard and Wolf, 2001), hence, interfere with daily life and well-being. However, other studies have focused attention on several *precursors* to PIU, such as neuroticism, agreeableness, conscientiousness, aggression, and impulsivity (Kim et al., 2008; Samarein et al., 2013). A recent effort to detect psychological *precursors* of PIU has pointed to a relatively new psychological phenomenon termed FoMO (Przybylski et al., 2013). FoMO is defined as an anxiety, whereby one is compulsively concerned that he/she might miss an opportunity for social interaction, a rewarding experience, profitable investment or other satisfying events. The mediating role of FoMO linking deficits in psychological needs to excessive use of social media has been assessed in several studies. For example, Abel et al. (2016) described FoMO as an overwhelming urge to be in two or more places at once, fueled by the fear that missing out on something could put a dent in one's happiness. In their study, FoMO was measured by inadequacy, irritability, anxiety, and self-esteem items. Results suggested significant differences in social media use across the measured levels of FoMO. Przybylski et al. (2013) study's results indicated that individuals who evidenced less satisfaction of the basic psychological needs for competence (efficacy), autonomy (meaningful choice), and relatedness (connectedness to others) also reported higher levels of FoMO and increased behavioral engagement with social media.

Several studies tested these connections in higher education learning environments. For example, Alt's (2015) study illustrated the robust mediating role of FoMO in explaining disruptive behaviors in the classroom enabled by using social media technology. In this study, the assumption that low levels of basic need satisfaction may relate to FoMO and social media engagement was tested. Path analysis results have confirmed the assumption that extrinsically and a-motivated undergraduate students are more likely to use social media tools available in the classroom for leisure. However, when those links were mediated by the FoMO variable, insignificant direct relations between the above academic motivations and social media engagement were detected. Hence, both motivational variables were positively related to FoMO, which in turn was associated with increased levels of social media engagement in the classroom. The robust mediating role of FoMO in explaining disruptive behaviors of social media use during lectures was also validated in a recent study (Alt, 2016). In this study, it was postulated that maladjustment to college, as indicative of students' decreasing well-being, could lead some toward excessive social media engagement for leisure during class. Path analysis results showed that the maladjustment to college variable is linked to social media use only insofar as it is linked to FoMO.

2.3. Deep and surface approaches to learning

The increased growth of Internet usages and their centrality in adolescents' lives, establish a need for more knowledge about the effect of these complex, online environments on adolescents' approaches to learning. These approaches refer to how students perceive themselves going about learning in a specific learning situation and focus on how intention and process are combined in students' deep or surface learning (Biggs et al., 2001). Marton and Säljö's (1976) seminal work

described a fundamental distinction in the manner in which students approached reading an academic article. They identified two different levels of processing while learning: deep and surface. Students who were focused on grasping the main points and memorizing them were defined as surface learners; whereas deep learners showed interest in the meaning behind a given topic, and attempted to deepen their understanding by linking it to other knowledge.

Haggis (2003) described and exemplified features of surface and deep learning approaches. Deep learners relate topic and ideas to prior knowledge and experiences. This competence is also acknowledged as a constructivist learning activity (Alt, 2014) which refers to the idea that content and skills should be understood within the framework of the learner's prior knowledge. Learners use their experience and knowledge to seek a clearer understanding of the learning materials, in contrast to surface learning which is confined to rote learning and memorizing facts (Price, 2014). The deep approach is considered an efficient way learners might use to deal with acquiring knowledge that grows at exponential proportions within change processes (Alt, 2015, 2016, 2017a, 2017b). Deep learners also think critically about a newly learned material, tie in information from other sources, and aim to understand the meaning behind the material. These competencies might be associated with self-regulated learning which refers to the student's ability to use internal control for learning, including setting their own goals, mediating new meanings from existing knowledge, and forming an awareness of current knowledge structures (De Clercq et al., 2014).

Self-regulated learning is often associated with meta-cognition. This term refers to the learners' ability to identify and select appropriate strategies, attend to and be aware of comprehension and task performance, and assess the processes and products of their learning, and revisit and revise their learning goals (Haggis, 2003). Another component of meta-cognition, other than cognitive regulation, is cognitive knowledge which pertains to the learners' ability to know about their own cognitive strengths and limitations as learners and factors affecting their cognition; their awareness and management of cognition, including knowledge about strategies, and knowledge about why and when to use a given strategy (Schraw et al., 2006; Whitebread et al., 2009).

Deep learners also create new arguments, understand logic based on new information, and recognize a structure in a given content (Haggis, 2003). These abilities of knowledge construction are also highly associated with the constructivist learning approach which perceives the individual as an active and responsible agent in his/her knowledge acquisition process (Brooks and Brooks, 1999). It may also be suggested that deep learners have the ability to continue to learn in order to cope with the changing and growing complexity of the context they studying. Scholars (Hammerness et al., 2005; Schwartz et al., 2005) assert that being an adaptive learner involves not simply knowing existing best practices, but also having the skills and will to search for new knowledge and practices when needed and be able to move beyond existing routines, rethink key ideas, practices, and values, in order to change and even adapt to changing circumstances. Lifelong learning often involves this kind of move - giving up old routines and transforming prior beliefs and practices. The last characteristic of deep learners deals with their motivation to learn (Haggis, 2003). The self-determination theory (SDT) (Deci and Ryan, 1985, 2008) defines intrinsic and extrinsic sources of motivation. Intrinsic motivation refers to internal factors, such as enthusiasm and pleasure experienced while engaging in a task. Whereas, extrinsic motivation refers to external factors, such as obtaining good grades or passing exams. Previous studies (e.g., Ryan and Connell, 1989) linked controlled (extrinsic) motivation to surface processing and weak coping strategies in the case of failing, whereas autonomous (intrinsic) motivation, associated with deep approach to learning, has been found correlated with the use of more information processing, high concentration while studying and better time management, and indirectly to higher academic achievement

(Vansteenkiste et al., 2005).

In contrast to deep learners, surface learners use unreflective approaches to learning, do not elaborate on facts, nor interact with content or ideas. Their intention is simply to reproduce parts of the content ideas and information accepted passively. They concentrate only on what is required for assessment, use rote learning, specify comprehended arguments, treat the task as a monotonous chore, have extrinsic motivation for learning, and aim to recite and regurgitate material inactively (Haggis, 2003).

The theory of learning approaches was further elaborated by Entwistle (1998/2012) and Biggs (1993). Biggs et al. (2001) have produced a two-factor scale, of deep and surface approaches, suitable for use by teachers in evaluating the learning approaches of their students. In the past decade, a multitude of empirical studies have pointed to several person- and environment- related correlates of students' learning approaches (Gijbels et al., 2014). For example, Platow et al. (2013) examined the role that students' discipline-related self-concepts may play in their deep and surface approaches to learning, their overall learning outcomes, and continued engagement in the discipline itself. Their study provided evidence for the validity of the deep learning approach construct, and for the theoretical claims associating a deep learning approach with an impact on self-concept and the educational value of encouraging a deep learning approach both for short-term academic performance and for continuing motivation to engage in the discipline. In a similar vein, Cano (2007) examined high school students' approaches to learning interrelationships with some personal and familial variables. Results indicated positive links between family's intellectual climate and the students' deep approach to learning. The latter was also associated with students' academic achievement, higher grades obtained by those students.

2.4. This study

Despite increased interest in and writing about FoMO, very little is empirically known about the phenomenon and its correlates in the context of learning approaches. Therefore, this study is aimed at revealing possible links between deep and surface learning approaches, FoMO, and PIU. PLS-SEM technique will be deployed to examine the following hypotheses which were based on two theoretical premises: first, the well- documented associations between controlled (extrinsic) motivation and surface learning (Ryan and Connell, 1989); and second, the robust mediating role of FoMO in explaining the links between psychological deficits, reflected by a-motivation and extrinsic motivation for learning, and excessive use of social media tools (Alt, 2015). In congruence with previous studies, it was hypothesized that:

H1. Surface learning approach will be associated with increased levels of PIU and FoMO.

H2. Deep learning approach will be associated with decreased levels of PIU and FoMO.

H3. FoMO will be detected as a mediator factor, associating between surface/deep learning and PIU.

H4. To further substantiate H3 an effort was made to assess the FoMO construct as a moderator. It was therefore postulated that FoMO will directly increase the strength of the relationship between the surface learning and PIU variables. Validating this hypothesis will cast doubt on the mediating role attributed to FoMO by previous studies, whereas rejecting it may further corroborate H3 as well as past findings.

3. Method

3.1. Participants and procedure

Data were gathered during 2016 (September–December) by

research assistants from 216, 13- to 18-year-old adolescents (51% males and 49% females), studying in two integrative public secondary and high schools in the Northern peripheral area of Israel (Western Galilee), at two different central cities out of seven. In each city, two public (secular) integrative schools exist, among other vocational, Arab, and religious schools, and might be considered representative of the Jewish secular public (integrative) schools in this area. The schools are located in middle-class areas. Each school includes six grades ranging from seventh grade to twelfth *grade*. In each grade level, an average of seven classes exist, each including about 22–36 students. 1000–1200 students are enrolled in each integrative school.

After receiving the school principals' approval to collect data, general information about the study and a request for parents' consent were sent through the school website. The number of permits received from both schools was 320, however, when the research assistants arrived at the schools, only 229 students have agreed to participate and fill out the questionnaire. It should be noted that 13 incomplete questionnaires were excluded from the analysis. Given the participants' voluntary involvement in the study, the sample's ability to accurately represent a target population cannot be guaranteed.

Prior to obtaining participants' consent and their parents', it was specified that the questionnaires were anonymous and that no pressure would be applied should they choose to return the questionnaire unfilled or incomplete. Finally, participants were assured that no specific identifying information would be processed.

3.2. Instrumentation

3.2.1. The Fear of Missing Out scale (FoMOs)

Based on a review of popular and industry writing on FoMO, Przybylski et al. (2013) created a 10-item scale, scored on a five-point Likert scale from 1 = *not at all true of me* to 5 = *extremely true of me*. The scale meant to reflect the fears, worries, and anxieties people may have in relation to being in (or out of) touch with the events, experiences, and conversations happening across their extended social environment. The scale measures the extent to which people feared missing out on rewarding experiences, activities, and methods of discourse, for example: 'I get worried when I find out my friends are having fun without me' ($\alpha = 0.82$).

3.2.2. The Short Problematic Internet Use Test (SPIUT)

The SPIUT questionnaire (Siciliano et al., 2015) consists of six items evaluating Problematic Internet Use. In this study, the participants were asked to address their social network usages. For example: 'Do you find that you are staying online longer than you intended?' The SPIUT questionnaire reflects these measures by assessing the frequency of occurrence throughout an individual's previous month on a five-point Likert scale from 0 = *never* to 4 = *very often* ($\alpha = 0.80$).

3.2.3. The Student Process Questionnaire (R-SPQ-2F)

The R-SPQ-2F (Biggs et al., 2001), consists of 20 items. The items are scored on a five-point Likert scale ranging from 1 = *almost never true* to 5 = *almost always true*. The participants were asked to indicate their approaches to studying. The surface approach to studying subscale measures students' tendency to meet the requirements of learning with a minimum effort, for example, 'I learn some things by rote, going over and over again until I know them by heart even if I do not understand them'. A deep approach to studying indicates that the student has an intrinsic interest in studying, for example, 'I find that at times studying gives me a feeling of deep personal satisfaction'. All the scale items were subjected to a principal component analysis followed by a Varimax rotation with an eigenvalue > 1.00 as a criterion for determining the number of factors. The analysis resulted in two factors, which accounted together for 45.20% of the variance. Table 1 presents the item loadings (> 0.40) on each of the factors and the computed internal consistencies (Cronbach's alpha) for each factor, indicating

Table 1
Factor loadings for the *R-SPQ-2F* questionnaire.

Item no.	Deep learning	Surface learning
E6	**0.744**	−0.132
E13	**0.734**	−0.255
E14	**0.718**	−0.116
E9	**0.700**	−0.078
E10	**0.694**	−0.013
E5	**0.669**	−0.111
E17	**0.632**	−0.117
E2	**0.632**	0.283
E1	**0.624**	−0.265
E18	**0.570**	−0.117
E7	−0.538	**0.470**
E12	−0.271	**0.715**
E11	0.063	**0.613**
E20	−0.049	**0.596**
E19	−0.380	**0.595**
E16	−0.319	**0.571**
E4	−0.023	**0.570**
E8	0.293	**0.487**
E15	−0.409	**0.484**
E3	−0.417	**0.475**
% variance	32.83	12.38
Cronbach's alpha	0.87	0.81

Bold items are those with loading > .40.

sufficient reliability results within the factors (between variable correlation $r = -0.469$, $p < .01$).

3.3. Data analysis

This study used Partial Least Squares Structural Equation Modeling (PLS-SEM; Hair et al., 2017). There are two main approaches to estimating the relationship in a structural equation model. The more widely applied is Covariance-based Structural Equation Modeling (CB-SEM) and PLS-SEM. A conceptual difference between the approaches relates to the way each method treats the latent variables included in the model. CB-SEM considers the constructs as common factors that explain the covariation between its indicators. The scores of these factors are not required in the estimation of model parameters. Unlike CB-SEM, PLS-SEM uses proxies to represent the constructs of interest, which reflect the weighted composites of indicators for a construct. Using weighted composites of indicator variables facilitates accounting for measurement error, thus making PLS-SEM superior compared with multiple regression using sum-scores. SmartPLS 3 software was used.

Table 2 shows the descriptive statistics of the research constructs and indicators. Following the general guidelines for skewness and kurtosis (suggesting that if the number is greater than +1 or lower than −1, then the distribution is skewed, flat or peaked, Hair et al., 2017), it can be learned that the distributions can be considered normal.

4. Results

In order to assess H1, H2, and H3, Model 1 (Fig. 1) was constructed. The model included four latent constructs represented in the model as cycles: deep learning, surface learning, FoMO, and PIU. The indicators are the directly measured proxy variables, represented as rectangles. Relationships between the constructs as well as between the constructs

Table 2
Descriptive statistics of the research constructs.

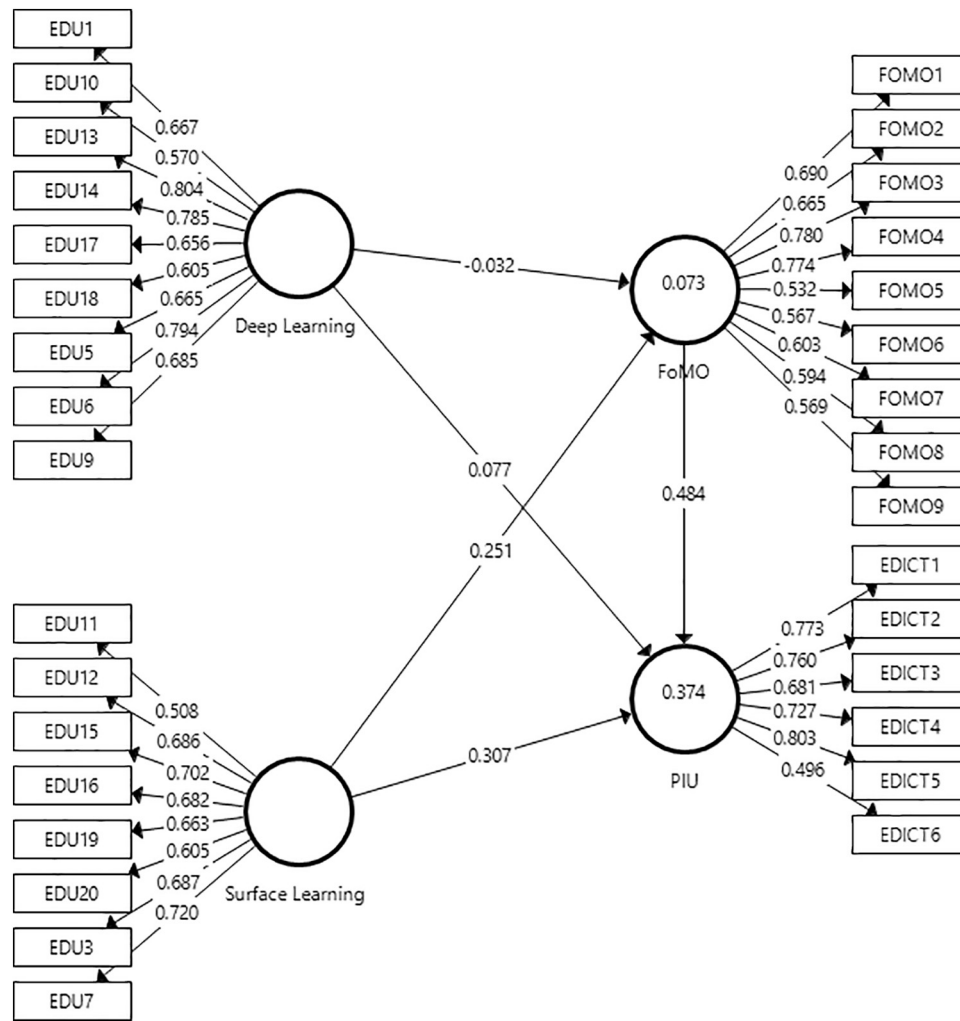| Construct	Mean	SD	Skewness	Kurtosis
FoMO	2.822	0.723	0.354	0.168
PIU	1.761	0.870	0.163	−0.611
Surface learning	2.759	0.728	0.298	−0.143
Deep learning	2.629	0.817	0.173	−0.507

Fig. 1. Model 1. Analysis results of the examination of H1–H3 by PLS-SEM.

and their assigned indicators are shown as arrows. In PLS-SEM, single-headed arrows, as shown between the constructs, are considered predictive relationships, and with strong theoretical support, can be construed as causal relationships. Paths were specified from the deep and surface learning constructs to FoMO, and from FoMO to PIU, thus FoMO has been entered into the model as a mediator. A mediation effect is created when a third construct (i.e., FoMO) intervenes between two other related constructs (i.e., PIU and surface learning). Further links were specified between the two constructs of learning approaches and PIU. For each scale, convergent validity assessment was based on the outer loadings of the indicators (should be > 0.40). Four items were omitted from the model due to low loading results < 0.40 (Hair et al., 2017), of which two surface learning items, a deep learning item, and a FoMO item. Another measure was the average variance extracted (AVE). AVE is defined as the grand mean value of the squared loadings of the indicators connected to the construct and is equivalent to the communality of a construct. An AVE value of 0.50 or higher indicates that, on average, the construct explains more than half of the variance of its related indicators (Hair et al., 2017). As can be learned from Table 4, convergent validity has been established for Model 1, with three AVE values slightly below the 0.50 threshold, and satisfactory reliability results.

Next, the structural model results have been examined, followed by the assessment of the mediating role of FoMO. The PLS-SEM analysis used path weighting scheme and a mean value replacement for missing values. The model evaluation included first, a collinearity examination

by Variance Inflation Factor (VIF) values of all sets of predictor constructs in the structural model. The results showed that the VIF values of all combinations of endogenous and exogenous constructs are below the threshold of 5 (Hair et al., 2017) ranging from 1.079 to 1.053. Therefore, collinearity among the predictor constructs is not a critical issue in this structural model. Second, the coefficient of determination (R^2) value was examined. R^2 for FoMO was found rather weak (0.073), the R^2 value for PIU was relatively higher (0.374) yet can be also considered weak (Hair et al., 2017). In addition to measuring the R^2 values, the change in the R^2 value when a specified exogenous construct is omitted from the model was used to evaluate its impact on the endogenous constructs. This measure is referred to as the f^2 effect size when values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effect (Cohen, 1988). According to the results, FoMO had a large effect size of 0.347 on PIU. The surface learning construct had a relatively low effect size of 0.046 on FoMO, and a medium effect size of 0.098 on PIU. The deep learning construct had very low effect sizes of 0.001 on FoMO, and of 0.006 on PIU. Finally, the blindfolding procedure was used to assess the predictive relevance (Q^2) of the path model. Values larger than 0 suggest that the model has predictive relevance for a certain endogenous construct (Hair et al., 2017). The Q^2 value of the FoMO construct was 0.027, whereas a relatively higher value was indicated for PIU (0.165). Based on these results, H1 and H2 were partially corroborated given the insignificant results for the deep learning construct correlates.

To test the mediating role of FoMO we run the bootstrap routine.

Table 3
Significance analysis of the direct and indirect effects for Model 1 and Model 2.

	Direct effect	95% confidence interval of the direct effect	*t* value	*p* value	Indirect effect	95% confidence interval of the indirect effect	*t* value	*p* value
Model 1								
FoMO - PIU	0.484	[0.390, 0.567]	10.541	0.000				
Surface learning - FoMO	0.251	[0.065, 0.418]	2.725	0.007				
Surface learning - PIU	0.307	[0.171, 0.421]	4.673	0.000	0.121	[0.029, 0.203]	2.694	0.007
Deep learning - FoMO	−0.032	[−0.250, 0.200]	0.287	0.774				
Deep learning - PIU	0.077	[−0.158, 0.212]	0.851	0.395				
Model 2								
FoMO - PIU	0.483	[0.399, 0.569]	11.164	0.000				
Surface learning - PIU	0.274	[0.186, 0.380]	5.540	0.000				
Surface learning ∗ FoMO - PIU	0.059	[−0.010, 0.141]	1.496	0.135				

Table 4
Result summary for Model 1.

Latent variable	Convergent validity	Internal constituency reliability	Composite reliability
	AVE	Cronbach's alpha	CR
	> 0.50	> 0.60	> 0.60
FoMO	0.419	0.823	0.864
PIU	0.510	0.804	0.859
Surface learning	0.435	0.814	0.859
Deep learning	0.486	0.870	0.893

Bootstrapping makes no assumptions about the shape of the variables' distribution or the sampling distribution and can be applied to small sample sizes (Hair et al., 2017). Table 3 presents the analysis results of the direct and indirect effects for Model 1. The results showed that both direct and indirect effects are significant only for the surface learning - FoMO - PIU connections, since none of the 95% confidence intervals includes zero. Non-significant coefficient results were indicated for the deep learning correlates (although a negative tendency was detected in relation with FoMO). Therefore, it can be concluded that FoMO partially mediates the relationships between surface learning and PIU. Moreover, the type of the partial mediation can be determined by the product of the direct effect and the indirect effect. Since both are positive, the sign of their product is also positive (i.e., $0.307 ∗ 0.121 = 0.037$). Hence we can conclude that FoMO represents complimentary mediation of the relationship from surface learning to PIU. H3 was partially confirmed.

Hypothesis H4 was tested by constructing Model 2 (Fig. 2). In this model, the moderating role of FoMO on the connection between surface learning and PIU was examined. A moderation effect occurs when the moderator changes the strength or the direction of a relationship between two constructs in the model. The SmartPLS 3 software offers an option to automatically include an interaction term. In this analysis, we aimed at disclosing the significant of the moderating effect by using the two-stage approach (Chin et al., 2003). To do so, we first included an interaction term (see surface learning ∗ FoMO construct in Fig. 2) and then proceeded with the bootstrap analysis. Table 3 (results for Model 2) presents the analysis results of the direct and interaction effects. The results show that the direct links between surface learning and PIU, and between FoMO and PIU are significant since the 95% confidence intervals do not include zero. However, the insignificant interaction result did not provide support that FoMO exerts a positive effect on the relationship between surface learning and PIU, therefore H4 was rejected.

5. Discussion

The overarching aim of this study was to detect possible relationships between learning approaches, FoMO, and PIU. PLS-SEM was deployed to discover possible links between the research factors, and the postulated mediating/moderating role of FoMO regarding the relationship between surface learning and PIU. The results showed a positive connection between FoMO and PIU. This finding seems to be consistent with other studies (Alt, 2015, 2016; Przybylski et al., 2013) which also found that increased use of social media tools might be informed by the fear of missing an opportunity for social interaction enabled by the Internet. Moreover, this research has also added to earlier findings (Alt, 2015) by showing that FoMO partially mediates the relationships between surface learning and PIU. The results represent a complimentary mediation of the relationship between surface learning and PIU by FoMO. While providing support for the hypothesized mediating relationship, this result also provides a cue that another mediator may have been overlooked whose indirect path has the same direction as the direct effect (Hair et al., 2017). An additional PLS-SEM analysis failed to establish a moderation role for the FoMO construct. Taken together, the analyses suggest that the strength of the surface learning approach-PIU relationship is constant and does not depend on the level of FoMO; however, FoMO as a mediator could partially explain the relationship between the two variables (Baron and Kenny, 1986). It might be inferred that surface learning approach could be linked to social media problematic use insofar as it is linked to FoMO, to some extent, or, alternatively, part of the surface learners' PIU might be explained by their increased FoMO.

Additional results that warrant mentioning are the non-significant path coefficients found between deep learning and the FoMO and PIU constructs. Thus, the postulated negative links between those constructs were not corroborated by the analysis. Nonetheless, the negative tendency shown for the deep learning - FoMO path may suggest that with a higher sample size the hypothesized negative links might be established.

Altogether, these results strengthen the notion that poor learning approaches might be connected to PIU for social interaction. Although learning approaches were not tested before in conjunction with PIU, these findings might be indirectly corroborated by previous studies (Akhter, 2013; Mishra et al., 2014; Türel and Toraman, 2015), showing inverse relations between Internet addiction and academic performance. However, the current study's results elaborate on previous studies by pointing to FoMO as a plausible mediating construct that might partially explain why surface learners tend toward problematic use of social media.

As lack of self-regulated learning lies at the core of surface approaches to learning, it may be inferred that students who fail to manage their learning efficiently also desire to stay continually connected with what others are doing. Self-regulation related to learning encompasses, among other variables, the monitoring and managing of one's behavior and environment. It includes self-discipline, effort, time management (Karabenick and Berger, 2013; Karabenick and Dembo, 2011; White and Bembenutty, 2013), and task management (single versus multitasking). The significant indirect link between surface learning and PIU through FoMO may lead to a plausible inference
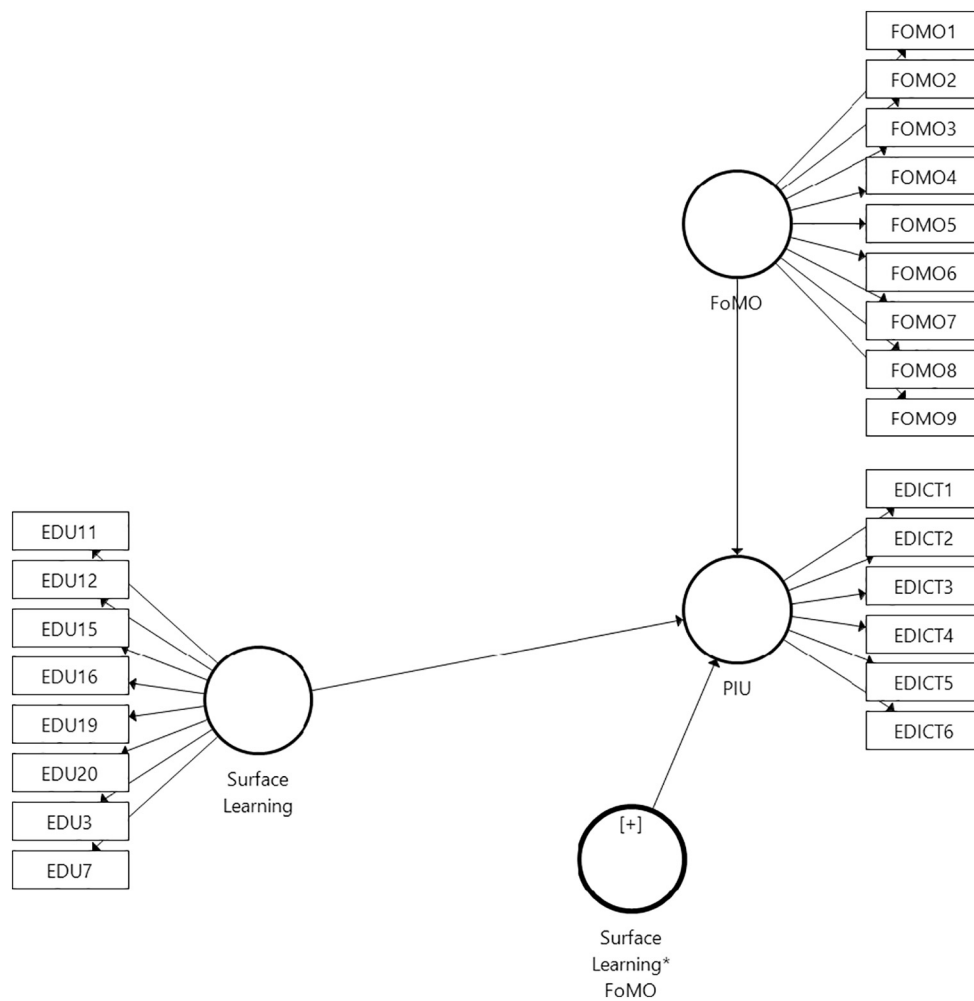
Fig. 2. Model 2. Analysis results of the examination of H4 by PLS-SEM.

according to which both FoMO and surface learning share a common core characteristic of decreased levels of self-regulation that might lead, at a certain level, to PIU.

5.1. Limitations and implications

The present work features several limitations that merit a mention and opens avenues for future research. This study was conducted in a single country and was limited to two schools located in two major cities; therefore, the results cannot necessarily be generalized to students of other regions. A cross-cultural validation of the results is needed to substantiate these findings.

The present study has been focused on the conception that student learning is taking place within the student. However, it has been recognized that approaches to learning are not merely characteristics of learners but are also determined by a relation between the learner and the context and that students adjust their approaches to learning depending on the requirements of the task (Evans, 2014). Thus, student learning should be construed within a teaching/learning context that functions as an 'open system' (Biggs, 1993). Future studies should consider examining the learning environment's possible impact on students' approaches to learning, and how it might intersect with FoMO and PIU.

As in this study the participants were asked to report on their general tendency to use social media, future efforts should specifically investigate in-class student behaviors regarding the use of social media, and how they may be related to FoMO and learning approaches. For

example, cell phones are viewed as an integral part of adolescents' life and culture and are overtly and covertly used in the classroom. Research suggests that students frequently use the cell phone during class time despite rules against doing so (Tindell and Bohlander, 2012). This device is recognized as an acceptable learning system (Lin et al., 2016) and appears capable of contributing to student learning and improved academic performance (Bull and McCormick, 2012; Tao and Yeh, 2013), however, is typically utilized for leisure rather than education (Lepp et al., 2015a; Lepp et al., 2013; Lepp et al., 2015b) and may disrupt learning within academic settings (Levine et al., 2007). Therefore, it might be worthwhile to assess the potential academic risks associated with high-frequency cell phone use.

With relation to the research empirical model, indeed PLS-SEM is suggested to be used when a researcher might want to predict target constructs and with a strong theoretical support, paths between constructs can be construed as causal relationships (Hair et al., 2017). However, the cross-sectional nature of the data in this study, and the rather small sample size can prevent definitive statements about causality. In fact, many relationships in the model are likely reciprocal. For example, although the analysis implies that surface approaches to learning might increase PIU, it is equally plausible that excessive and problematic social media engagement might disrupt students' learning processes.

5.2. Conclusions and implications

The present study associates between students' FoMO and their

inability, to some extent, to self-regulate their learning. Self-regulation consists of steering the learning process by using strategies such as information-seeking, self-evaluation, monitoring, and goal-setting (de Clercq et al., 2014). As both FoMO and surface learning might share a common core characteristic of decreased levels of self-regulation, it seems worthwhile to address the latter during the learning processes and embrace learning environments in which the teacher is perceived as the facilitator of learning, who guide and support the learners. In these processes, students are given opportunities to actively engage in self-regulated learning. Having students acquire and practice skills of self-regulation might entail the promotion of analogous skills that can help them control their levels of FoMO, and consequently their PIU behavior. It also seems important to address self-regulation in future studies and measure its effect on the empirical model constructs assessed in this study. Adding this variable to this research complimentary mediation model could give further insights regarding its possible mediating role in linking surface learning to PIU.

This study elaborates on previous work by showing that FoMO might play a mediating role linking poor learning approaches to problematic use of social media tools. Nevertheless, the research model suggested by this study was tested for the first time, and had relatively low coefficients of determination results, meaning that the results cannot necessarily be generalized. Larger sample studies and the inclusion of additional constructs into the empirical model are needed to corroborate the suggested findings.

Conflicts of interest

None.

Appendix A

The Fear of Missing Out scale (FoMOs)

1. I fear others have more rewarding experiences than me.
2. I fear my friends have more rewarding experiences than me.
3. I get worried when I find out my friends are having fun without me.
4. I get anxious when I don't know what my friends are up to.
5. It is important that I understand my friends "in jokes."
6. Sometimes, I wonder if I spend too much time keeping up with what is going on.
7. It bothers me when I miss an opportunity to meet up with friends.
8. When I have a good time it is important for me to share the details online (e.g. updating status).
9. When I miss out on a planned get-together it bothers me.
10. When I go on vacation, I continue to keep tabs on what my friends are doing.

The Short Problematic Internet Use Test (SPIUT)

1. Do you find that you are staying online longer than you intended?
2. Have you neglected homework because you are spending more time online?
3. Have you been reprimanded by your parents or your friends about how much time you spend online?
4. Have you lost sleep due to logging in late at night?
5. Do you feel nervous when you are offline and is that feeling relieved when you do go back online?
6. Have you chosen to spend more time online rather going out with your friends?

The Student Process Questionnaire (R-SPQ-2F)

1. I find that at times studying gives me a feeling of deep personal satisfaction.
2. I find that I have to do enough work on a topic so that I can form my

own conclusions before I am satisfied.
3. My aim is to pass the course while doing as little work as possible.
4. I only study seriously what's given out in class or in the course outlines.
5. I feel that virtually any topic can be highly interesting once I get into it.
6. I find most new topics interesting and often spend extra time trying to obtain more information about them.
7. I do not find my course very interesting so I keep my work to the minimum.
8. I learn some things by rote, going over and over them until I know them by heart even if I do not understand them.
9. I find that studying academic topics can at times be as exciting as a good novel or movie.
10. I test myself on important topics until I understand them completely.
11. I find I can get by in most assessments by memorizing key sections rather than trying to understand them.
12. I generally restrict my study to what is specifically set as I think it is unnecessary to do anything extra.
13. I work hard at my studies because I find the material interesting.
14. I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes.
15. I find it is not helpful to study topics in depth. It confuses and wastes time, when all you need is a passing acquaintance with topics.
16. I believe that lecturers shouldn't expect students to spend significant amounts of time studying material everyone knows won't be examined.
17. I come to most classes with questions in mind that I want answering.
18. I make a point of looking at most of the suggested readings that go with the lectures.
19. I see no point in learning material which is not likely to be in the examination.
20. I find the best way to pass examinations is to try to remember answers to likely questions.

References

Abel, J.P., Buff, C.L., Burr, S.A., 2016. Social media and the fear of missing out: scale development and assessment. J. Bus. Econ. Res. (Online) 14 (1), 33. Retrieved from: http://ezproxy.kinneret.ac.il:2067/docview/1757523519?accountid=39607.

Akhter, N., 2013. Relationship between Internet addiction and academic performance among university undergraduates. Educ. Res. Rev. 8, 1793–1796.

Alt, D., 2014. The construction and validation of a new scale for measuring features of constructivist learning environments in higher education. Frontline Learn. Res. 2 (3). http://dx.doi.org/10.14786/flr.v2i2.68.

Alt, D., 2015. College students' academic motivation, media engagement and fear of missing out. Comput. Hum. Behav. 49, 111–119.

Alt, D., 2016. Students' wellbeing, fear of missing out, and social media engagement for leisure in higher education learning environments. Curr. Psychol. http://dx.doi.org/10.1007/s12144-016-9496-1.

Alt, D., 2017a. Students' social media engagement and fear of missing out (FoMO) in a diverse classroom. J. Comput. High. Educ. 29 (2), 388–410.

Alt, D., 2017b. College students' perceived learning environment and their social media engagement in activities unrelated to class work. Instr. Sci. 45, 623–643.

American Psychiatric Association, 2013. Diagnostic and Statistical Manual of Mental Disorders (DSM-5®). American Psychiatric Pub Retrieved from: www.dsm5.org/ProposedRevision/Pages/SubstanceUseandAddictiveDisorders.aspx.

Baron, R.M., Kenny, D.A., 1986. The moderator-mediator variable distinction in social psychological research: conceptual, strategic, and statistical considerations. J. Pers. Soc. Psychol. 51, 1173–1182.

Beard, K.W., Wolf, E.M., 2001. Modification in the proposed diagnostic criteria for internet addiction. Cyberpsychol. Behav. 4, 377–383.

Biggs, J.B., 1993. What do inventories of students' learning process really measure? A theoretical review and clarification. Br. J. Educ. Psychol. 63, 3–19.

Biggs, J.B., Kember, D., Leung, D.Y.P., 2001. The revised two-factor study process questionnaire: R-SPQ-2F. Br. J. Educ. Psychol. 71, 133–149.

Brooks, J.G., Brooks, M.G., 1999. In Search of Understanding: The Case for Constructivist Classrooms. Association for Supervision and Curriculum Development, Alexandria, VA.

Bull, P., McCormick, C., 2012. Mobile learning: integrating text messaging into a

community college pre-algebra course. Int. J. E-learn. 11, 233–245.

Cano, F., 2007. Approaches to learning and study orchestrations in high school students. Eur. J. Psychol. Educ. 22 (2), 131–151.

Carlisle, K.L., Carlisle, R.M., Polychronopoulos, G.B., Goodman-Scott, E., Kirk-Jenkins, A., 2016. Exploring internet addiction as a process addiction. J. Ment. Health Couns. 38, 170–182.

Chen, S.Y., Tzeng, J.Y., 2010. College female and male heavy internet users' profiles of practices and their academic grades and psychosocial adjustment. Cyberpsychol. Behav. Soc. Netw. 13, 257–262.

Chen, L.Y., Hsiao, B., Chern, C.C., Chen, H.G., 2014. Affective mechanisms linking internet use to learning performance in high school students: a moderated mediation study. Comput. Hum. Behav. 35, 431–443.

Chen, X., Pan, Y., Guo, B., 2016. The influence of personality traits and social networks on the self-disclosure behavior of social network site users. Internet Res. 26 (3), 566–586.

Chin, W.W., Marcolin, B.L., Newsted, P.R., 2003. A partial least squares latent variable modeling approach for measuring interaction effects: results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. Inf. Syst. Res. 14, 189–217.

Chung, T., 2013. Adolescent substance use: symptoms and course. In: Miller, P.E. (Ed.), Principles of Addiction: Comprehensive Addictive Behaviors and Disorders. vol. 1. Elsevier, San Diego, CA, pp. 97–106.

Cohen, J., 1988. Statistical Power Analysis for the Behavioral Sciences. Lawrence Erlbaum, Mahwah, NJ.

De Clercq, M., Galand, B., Frenay, M., 2014. Learning processes in higher education: providing new insights into the effects of motivation and cognition on specific and global measures of achievement. In: Gijbels, D., Donche, V., Richardson, J.T.E., Vermunt, J.D. (Eds.), Learning Patterns in Higher Education: Dimensions and Research Perspectives. Routledge and EARLI, London and New York, pp. 141–162.

Deci, E.L., Ryan, R.M., 1985. Intrinsic Motivation and Self-determination in Human Behavior. Plenum, New York.

Deci, E.L., Ryan, R.M., 2008. Self-determination theory: a macrotheory of human motivation, development, and health. Can. Psychol. 49, 182–185.

Entwistle, N., 1998/2012. Styles of Learning and Teaching. An Integrated Outline of Educational Psychology for Students, Teachers and Lecturers. Routledge, New York.

Evans, C., 2014. Exploring the use of a deep approach to learning with students in the process of learning to teach. In: Gijbels, D., Donche, V., Richardson, J.T.E., Vermunt, J.D. (Eds.), Learning Patterns in Higher Education: Dimensions and Research Perspectives. Routledge and EARLI, London and New York, pp. 187–213.

Flisher, C., 2010. Getting plugged in: an overview of internet addiction. J. Pediatr. Child Health 46, 557–559.

Gijbels, D., Donche, V., Richardson, J.T.E., Vermunt, J.D. (Eds.), 2014. Learning Patterns in Higher Education: Dimensions and Research Perspectives. Routledge and EARLI, London and New York.

Greenfield, D.N., 1999. Psychological characteristics of compulsive internet use: a preliminary analysis. Cyberpsychol. Behav. 2, 403–412.

Haggis, T., 2003. Constructing images of ourselves? A critical investigation into 'approaches to learning' research in higher education. Br. Educ. Res. J. 29, 89–104.

Hair Jr., J.F., Hult, G.T.M., Ringle, C.M., Sarstedt, M., 2017. A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 2nd ed. Sage, Thousand Oaks.

Hammerness, K., Darling-Hammond, L., Bransford, J., Berliner, D., Cochran-Smith, M., McDonald, M., Zeichner, K., 2005. How teachers learn and develop. In: DarlingHammond, L., Bransford, J. (Eds.), Preparing Teachers for a Changing World: What Teachers Should Learn and Be Able to Do. Jossey-Bass, San Francisco, pp. 358–389.

Huang, H., Leung, L., 2009. Instant messaging addiction among teenagers in China: shyness, alienation, and academic performance decrement. Cyberpsychol. Behav. 12, 675–679.

Karabenick, S.A., Berger, J., 2013. Help seeking as a self-regulated learning strategy. In: Bembenutty, H., Cleary, T.J., Kitsantas, A. (Eds.), Applications of Self-regulated Learning Across Diverse Disciplines: A Tribute to Barry J. Zimmerman. Information Age Publishing, Charlotte, NC, pp. 237–261.

Karabenick, S.A., Dembo, M.H., 2011. Understanding and facilitating self-regulated help seeking. New Dir. Teach. Learn. 2011 (126), 33–43.

Kim, Y., Jeong, J.S., 2015. Personality predictors for the use of multiple internet functions. Internet Res. 25 (3), 399–415.

Kim, E.J., Namkoong, K., Ku, T., Kim, S.J., 2008. The relationship between online game addiction and aggression, self-control and narcissistic personality traits. Eur. Psychiatry 23 (3), 212–218.

Lenhart, A., Duggan, M., Perrin, A., Stepler, R., Rainie, L., Parker, K., 2015a. Teens, Social Media & Technology Overview 2015: Smartphones Facilitate Shifts in Communication Landscape for Teens. Pew Research Center Retrieved from. http://www.pewInternet.org/2015/04/09/teens-social-media-technology-2015/.

Lenhart, A., Smith, A., Anderson, M., Duggan, M., Perrin, A., 2015b. Teens, Technology & Friendships: Video Games, Social Media and Phones Play an Integral Role in How Teens Meet and Interact With Friends. Pew Research Center Retrieved from. http://www.pewInternet.org/2015/08/06/teens-technology-and-friendships/.

Lepp, A., Barkley, J.E., Sanders, G.J., Rebold, M., Gates, P., 2013. The relationship between cell phone use, physical and sedentary activity, and cardiorespiratory fitness in a sample of U.S. college students. Int. J. Behav. Nutr. Phys. Act. 10 (1), 79. Retrieved from: http://www.ijbnpa.org/content/10/1/79.

Lepp, A., Barkley, J.E., Karpinski, A.C., 2015a. The relationship between cell phone use and academic performance in a sample of US college students. SAGE Open 5 (1) (2158244015573169).

Lepp, A., Li, J., Barkley, J.E., Salehi-Esfahani, S., 2015b. Exploring the relationships between college students' cell phone use, personality and leisure. Comput. Hum. Behav.

43, 210–219.

Levine, L.E., Waite, B.M., Bowman, L.L., 2007. Electronic media use, reading, and academic distractibility in college youth. Cyberpsychol. Behav. 10, 560–566.

Li, D., Li, X., Wang, Y., Zhao, L., Bao, Z., Wen, F., 2013. School connectedness and problematic internet use in adolescents: a moderated mediation model of deviant peer affiliation and self-control. J. Abnorm. Child Psychol. 41, 1231–1242.

Lin, H.H., Lin, S., Yeh, C.H., Wang, Y.S., 2016. Measuring mobile learning readiness: scale development and validation. Internet Res. 26 (1), 265–287.

Marton, F., Säljö, R., 1976. On qualitative differences in learning: 1-outcome and process. Br. J. Educ. Psychol. 46, 4–11.

Mishra, S., Draus, P., Goreva, N., Leone, G., Caputo, D., 2014. The impact of internet addiction on university students and its effect on subsequent academic success: a survey based study. Issues Inf. Syst. 15, 344–352.

Moreno, M.A., Jelenchick, L., Cox, E., Young, H., Christakis, D.A., 2011. Problematic internet use among US youth: a systematic review. Arch. Pediatr. Adolesc. Med. 165, 797–805.

Platow, M.J., Mavor, K.I., Grace, D.M., 2013. On the role of discipline related self-concept in deep and surface approaches to learning among university students. Instr. Sci. 41, 271–285.

Price, L., 2014. Modelling factors for predicting student-learning outcomes in higher education. In: Gijbels, D., Donche, V., Richardson, J.T.E., Vermunt, J.D. (Eds.), Learning Patterns in Higher Education: Dimensions and Research Perspectives. Routledge and EARLI, London and New York, pp. 56–77.

Przybylski, A.K., Murayama, K., DeHaan, C.R., Gladwell, V., 2013. Motivational, emotional, and behavioral correlates of fear of missing out. Comput. Hum. Behav. 29, 1841–1848.

Qiaoli, J., 2014. Internet addiction among young people in China: internet connectedness, online gaming, and academic performance decrement. Internet Res. 24 (1), 2–20.

Ryan, R.M., Connell, J.P., 1989. Perceived locus of causality and internalization: examining reasons for acting in two domains. J. Pers. Soc. Psychol. 57, 749–761.

Ryan, T., Chester, A., Reece, J., Xenos, S., 2014. The uses and abuses of Facebook: a review of Facebook addiction. J. Behav. Addict. 3, 133–148.

Samarein, Z.A., Far, N.S., Yekleh, M., Tahmasebi, S., Yaryari, F., Ramezani, V., Sandi, L., 2013. Relationship between personality traits and internet addiction of students at Kharazmi University. Int. J. Psychol. Behav. Res. 2 (1), 10–17.

Sasson, H., Erez, R., Elgali, Z., 2012. Perceptions and attitudes toward risk behaviors, among adolescents. Retrieved from: http://www.holon.muni.il/Lists/List6/DispForm.aspx?ID=880 (Hebrew).

Schraw, G., Crippen, K.J., Hartley, K., 2006. Promoting self-regulation in science education: metacognition as part of a broader perspective on learning. Res. Sci. Educ. 36, 111–139.

Schwartz, D.L., Bransford, J.D., Sears, D.L., 2005. Efficiency and innovation in transfer. In: Mestre, J. (Ed.), Transfer of Learning From a Modern Multidisciplinary Perspective. Information Age Publishing, CT, pp. 1–51.

Siciliano, V., Bastiani, L., Mezzasalma, L., Thanki, D., Curzio, O., Molinaro, S., 2015. Validation of a new short problematic internet use test in nationally representative sample of adolescents. Comput. Hum. Behav. 45, 177–184.

Tao, Y., Yeh, C.R., 2013. Transforming the personal response system to a cloud voting service. In: Uesugi, S. (Ed.), IT Enabled Services. Springer, Verlag, Austria, pp. 139–156.

Tindell, D.R., Bohlander, R.W., 2012. The use and abuse of cell phones and text messaging in the classroom: a survey of college students. Coll. Teach. 60, 1–9.

Türel, Y.K., Toraman, M., 2015. The relationship between internet addiction and academic success of secondary school students. Anthropologist 20, 280–288.

van den Eijnden, R.J., Spijkerman, R., Vermulst, A.A., van Rooij, T.J., Engels, R.C., 2010. Compulsive internet use among adolescents: bidirectional parent-child relationships. J. Abnorm. Child Psychol. 38, 77–89.

van den Eijnden, R.J., Lemmens, J.S., Valkenburg, P.M., 2016. The social media disorder scale: validity and psychometric properties. Comput. Hum. Behav. 61, 478–487.

van Rooij, A.J., Kuss, D.J., Griffiths, M.D., Shorter, G.W., Schoenmakers, M.T., van De Mheen, D., 2014. The (co-)occurrence of problematic video gaming, substance use, and psychosocial problems in adolescents. J. Behav. Addict. 3, 157–165.

Vansteenkiste, M., Zhou, M., Lens, W., Soenens, B., 2005. Experiences of autonomy and control among Chinese learners: vitalizing or immobilizing. J. Educ. Psychol. 97, 468–483.

Wąsiński, A., Tomczyk, L., 2015. Factors reducing the risk of internet addiction in young people in their home environment. Child Youth Serv. Rev. 57, 68–74.

Weinstein, A., Lejoyeux, M., 2010. Internet addiction or excessive internet use. Am. J. Drug Alcohol Abuse 36, 277–283.

White, M.C., Bembenutty, H., 2013. Not all avoidance help seekers are created equal: individual differences in adaptive and executive help seeking. SAGE Open 3 (2), 1–14.

Whitebread, D., Coltman, P., Pasternak, D.P., Sangster, C., Grau, V., Bingham, S., Almeqdad, Q., Demetriou, D., 2009. The development of two observational tools for assessing metacognition and self-regulated learning in young children. Metacogn. Learn. 4 (1), 63–85.

Wu, C.H., Chen, S.C., 2015. Understanding the relationships of critical factors to Facebook educational usage intention. Internet Res. 25 (2), 262–278.

Young, K.S., 1998. Internet addiction: the emergence of a new clinical disorder. Cyberpsychol. Behav. 1, 237–244.

Zhu, Y.Q., Chen, L.Y., Chen, H.G., Chern, C.C., 2011. How does internet information seeking help academic performance? The moderating and mediating roles of academic self-efficacy. Comput. Educ. 57, 2476–2484.

Dorit Alt (female) is a Senior Lecturer and Head of the Education and Community

Department at the Kinneret College on the Sea of Galilee. Dr. Alt is specialized in the field of constructivist learning environments in the era of information. Her research work includes research on digital and media literacy skills among adolescents, the construction and validation of several innovative scales, to map and assess different aspects of constructivist learning environments, and the measurement of the connection between these environments and psychological, behavioral, cultural, social, and ethical aspects.

Meyran Boniel-Nissim (female) has a PhD. from Haifa University. Her Ph.D. Dissertation specialized on "Cyber Psychology". Meyran Boniel-Nissim teaches how technology can be used for support, therapy, and education. In her courses, she combines between varied teaching methods (problem-based learning, distance learning, blended learning). Dr. Boniel-Nissim is an active researcher in the research program of the World Health Organization (HBSC-WHO). Her research interests are focused on opportunities and risks of electronic media communication.